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INFERENTIAL PROBLEMS FOR A CLASS OF DISCRETE-TIME HYBRID SYSTEMS PART III: FAULT DIAGNOSIS

D.Sarkar [*] **P.Bhowal** [**] **A.Basu** [***] **S.Mukhopadhyay** [****]

[*] *Dept. of Computer Science and Engg.Indian Institute of Technology*
[**] *Dept. of Computer Science and Engg., Indian Institute of Technology*
[***] *Dept. of Computer Science and Engg., Indian Institute of Technology*
[****] *Dept. of Electrical Eng., Indian Institute of Technology, Kharagpur, India, 721302*

Abstract: This paper, the last part of our three-part contribution, is concerned with the diagnosis of faults in the discrete-time hybrid system model, described in Part I. The original contributions of the paper are as follows. Faults have been modelled in terms of Activity States labelled as faulty. The problem of diagnosis is formulated based on that of state estimation, as described in Part II. The timed sequence of the estimates of the current state of the overall system from the Observer is then used for fault diagnosis.

Keywords: Hybrid Systems, Discrete-time Systems, Systems Modelling, State Estimation, Fault Diagnosis

1. INTRODUCTION

Fault detection and diagnosis (FDD) has been the subject of much research from the area of DEDS (Sampath *et al.*, 1995), (Sampath *et al.*, 1996), (Mukhopadhay *et al.*, 2000*a*), (Bhowal *et al.*, 2000), (Mukhopadhay *et al.*, 2000*b*) and continuous dynamics. However work on FDD based on Hybrid System Models has started recently (Basseville *et al.*, 1997), (Gao and Xu, 1999), (McIlraith *et al.*, 2000).

In this paper we have developed a fault detection method based on the Hybrid System formalism discussed in our companion paper (Bhowal *et al.*, 2002*a*), (Bhowal *et al.*, 2002*b*), where the concept of restricted measurement and model abstraction based on limited measurement has been discussed. Fault diagnosis notions are built on the measurement reduced hybrid model and conditions of diagnosability are discussed.

Advantages of our framework over (Sampath *et al.*, 1995), (Sampath *et al.*, 1996), are that we can determine fault detection delay and also diagnose the faults that remains in transitions with the same source and destination states but with different timing features, using the same set of sensors.

This paper is organized as follows. Section 2 discusses fault modeling. Section 3 discuss diagnosability with observer estimates and Section 4 discusses how a timed sequence of observer estimate can be used for diagnosis. Section 5 is concerned with estimation of the detection delay, while section 6 concludes this paper.

2. NOTATIONS AND DEFINITIONS

Consider after (Bhowal *et al.*, 2002*a*), (Bhowal *et al.*, 2002*b*), the observer $O =< N, A >$, constructed from the composite process model after measurement restriction.

Let $F = \{f_1, f_2, ...f_i......f_n\}$ be the set of all possible faults. A particular fault f_i can occur only in one component.

If a fault f_i occurs in a component C, C will be in a specified faulty activity state, denoted as c_{f_i}. For example, if a heater develops a fault, namely Heater STUCK OFF, then $C_{f_i} = H_{SF}$.

A composite activity state is an ordered tuple of the activity states of all components.

Let the l^{th} member of the tuple be the activity state of the component C. If a fault f_i has occurred in C, then c_{f_i} will occur in the l^{th} position of the state tuple. We can denote one composite activity state x_j containing fault f_i as x_{jf_i}. Similarly, an activity state x_k containing multiple faults $f_i, f_j, ...f_n$, from different components is denoted as $x_{kf_if_j..f_n}$, where f_i to f_n are the faults of components in the composite activity state x_k.

Therefore, each composite activity state $x \in X$ is now marked with either n (for normal) or a fault label $f_i \in \{f_1....f_n\}$ or a multiple fault tag $(f_i..f_j) \in 2^{\{f_1....f_n\}}$.

Let X_{f_k} denote the set of all the composite activity states corresponding to the fault f_k. It is to be noted that a state $x_{f_kf_i}$ simultaneously belongs to $X_{f_kf_i}$, X_{f_i} and X_{f_k}. Let n_{f_i} denote a node of the observer O, containing at least one state $x_j \in X_{f_i}$. The set of all n_{f_i}s is denoted as N_{f_i}.

Definition 1. **f_i-certain node**
An observer node n is called and f_i-certain node if and only if $n \subseteq X_{f_i}$. An f_i-certain node is denoted as $n_{\otimes f_i}$.

Definition 2. **Trajectories of O:**
A trajectory γ of O is a sequence of nodes $< n_1, n_2, ...n_i, n_{i+1}.. >$ of O where for $k \geq 1$, $< n_k, n_{k+1} >$ is an arc of the observer. The set of all trajectories are denoted as Γ.

Definition 3. **f_i -trajectory (γ_{f_i}):**
A trajectory $\gamma \in \Gamma$ is an f_i-trajectory if $\forall n \in \gamma \Rightarrow n \in N_{f_i}$. An f_i-trajectory is denoted as γ_{f_i}

After the occurrence of a permanent fault, the system should follow an $f_i - trajectory$.

Definition 4. **f_i -uncertain loop:($\psi_{\otimes f_i}$):**
An f_i-uncertain loop is a loop formed by an f_i-trajectory γ_{f_i} which does not contain any n such that $n \subseteq X_{f_i}$ node. An f_i-uncertain loop is denoted as $\psi_{\otimes f_i}$.

If the system estimate moves along such an f_i-uncertain loop, then fault f_i cannot be diagnosed, because the system may not exit from such a loop.

In this paper we are considering permanent faults only.

3. DIAGNOSABILITY USING THE OBSERVER

In general a system is diagnosable for a fault f_i, if and only if the occurrence of the fault is detectable within a finite delay with the observation of measurable variables. The definition of diagnosability is given below.

Definition 5. **f_i-diagnosability:**
A system is f_i-diagnosable for fault f_i with respect to its observer O, for a given measurement restriction if and only if the following conditions hold.

(1) $\exists n_{\oplus f_i} \in N$
(2) $\forall n_{kf_i} \in N \quad \forall \gamma_{f_i} =< n_{kf_i}, ...n_{lf_i} > \in \Gamma \Rightarrow (n_{lf_i} = n_{\oplus f_i})$
(3) $\nexists \psi_{\otimes f_i}$

In the above definition, the first point says that for a system to be diagnosable for fault f_i, the observer is required to have an f_i-certain node. The second point says that, from all nodes containing an $x \in X_{f_i}$ all the f_i-trajectories should reach some f_i-certain node . The third point states that there is no f_i-uncertain loop in the trajectory. This implies that all the trajectories, characterised by the second clause are finite.

If a system is f_i-diagnosable for a fault f_i, then the fault f_i can be detected within a finite time. In most of the real life systems there will be f_i-uncertain loops and hence the **Definition 5** of f_i-diagnosability serves only as a sufficient condition for diagnosability and not a necessary one.

For practical systems, presence of $\psi_{\otimes f_i}$ loop is natural, especially, when we have multiple components, required to be controlled and they are not influencing each other.

Considering such a situation, a weaker definition of diagnosability, termed Pf_i-diagnosability, and its associated definitions are introduced.

Let $\Im_{dP}$ be the set of observer arcs, defined as follows

$$\Im_{dP} = \{a | a \in A \;\; and \;\; a \;\; changes \;\; some \;\; measurable \;\; variable \;\; of \;\; P\}$$

Definition 6. **Pf_i -trajectory(γ_{Pf_i}):**
A trajectory $\gamma \in \Gamma$ is a Pf_i-trajectory if the following conditions holds

(1) f_i pertains to a component P
(2) $\forall n \in \gamma \Rightarrow n \in N_{f_i}$
(3) $\exists a \in \gamma \;\; and \;\; a \in \Im_{dP}$

A Pf_i-trajectory of O is denoted as γ_{Pf_i}.

Definition 7. **Pf_i -uncertain loop ($\psi_{\otimes Pf_i}$):**
A Pf_i-trajectory γ_{Pf_i} is a Pf_i-uncertain loop if γ_{Pf_i} is a loop and $\forall n \in \gamma_{Pf_i} \Rightarrow n \in N_{f_i}$ which does not contain any f_i-certain node.

A Pf_i-loop in O is denoted as ψ_{Pf_i} and an Pf_i-uncertain loop is denoted as $\psi_{\otimes Pf_i}$.

For diagnosis of a fault f_i pertaining to P, it is necessary that all the γ_{Pf_i} trajectories should end into some f_i-certain node. Based on this a weaker definition of diagnosability is given below.

Definition 8. Pf_i**-diagnosability:**
A system is Pf_i-diagnosable for fault of type f_i with respect to its observer O, if and only if the following conditions hold.

(1) $\exists n_{\oplus f_i}$
(2) $\forall n_{kf_i} \in N \quad \forall \gamma_{Pf_i} =< n_{kf_i}, ...n_{lf_i} > \in \Gamma \Rightarrow (n_{lf_i} = n_{\oplus f_i})$
(3) $\nexists \psi_{\otimes Pf_i}$

The second clause above necessitates that there be a transition from each n_{f_i} node except for an f_i-certain node. But an n_{f_i}-node may contain a sink state of the composite model [1]. In such a case, upon occurrence of the fault, no out going transition shall be activated in O. Thus, if nonoccurrence of outgoing transitions, over a finite time, can be ascertained, then the fault can be diagnosed. In order to capture this situation, we redefine the f_i-certain node. A concept of $w - transition$ is introduced first.

A transition is called $w - transition$ (wait transition), when the enabling condition depends on external agents.

Definition 9. f_i **-certain node:**
A node n is called f_i-certain node iff
1. $n \subseteq X_{f_i}$, or
2. $(n \cap X_{f_i} = x_{f_i} \;\; and \;\; x_{f_i} \;\; is \;\; a \;\; sink \;\; state) \wedge (there \;\; is \;\; no \;\; w - transition \;\; from \;\; n)$

An f_i-certain node is denoted as $n_{\oplus f_i}$ as before.

In the second clause above, $n \cap X_{f_i} = x_{f_i}$ indicates that the node n contains only one activity state x_{f_i} pertaining to the fault of type f_i. If such a node exists and the fault of f_i occurs, then the fault shall be diagnosed, if none of the outgoing transitions from n occurs within their valid period. However, if a wait transition (w) is defined from the node, then it is not possible to detect the non-occurrence of wait transition . The non-occurrence of a $w - transition$ can not be detected within a finite time. However the occurrence of an $w - transition$ is dependent on external events and hence it is not possible to associate any time limit, on expiry of which it can be said that the $w - transition$ is not going to occur. Therefore if a $w - transition$ is defined from the node, then it can not be $f_i - certain$.

The goal of obtaining an on-line diagnoser, however, still remains illusive because the mechanism to detect nonoccurrence of transitions is yet to be addressed. This mechanism necessitates estimating various time parameters. For example, given an entry transition to a node n, it is necessary to know the maximum waiting time after which the observer can be sure that no outward transition from n will take place in future. Another time parameter needed is the dwell-time inside a node n for a given pair of incoming and outgoing transitions of n. These time parameters are required not only for on-line observer construction but also for making a conservative estimate of the detection delay of Pf_i-diagnosable faults.

In order to achieve the above goals, we generate sub nodes of n, using a process called time sequencing of n, as explained in the next section. Eventually it may happen that some of the subsets become f_i-certain. This creates the possibility of detection of additional faults or early detection of faults, which is otherwise not detectable from the observer O without time sequencing.

Based on the above definition, the diagnosability of a system w.r.t. all faults is now defined.

Definition 10. **Diagnosability:**
A system is diagnosable if and only if it is Pf_i-diagnosable for all faults $f_i \in F$.

4. TIME SEQUENCING OF THE OBSERVER NODES

The information contained in l_τ and u_τ of a transition τ has been used in categorising measurable transitions as distinguishable or not. Based on these timing information, we can further refine the state estimation of an uncertainty node of the observer O with passage of time. This process is termed as *time sequencing* of nodes. Time sequencing of nodes is based on the following properties

4.1 *Definitions*

The following definitions are necessary in order to explain the time sequencing method.

Definition 11. **Early exit data state** $(\overline{\sigma}_\tau)$ **of** τ **:**
Early exit data state $(\overline{\sigma}_\tau)$ of a transition $\tau =< x, x^+, e_\tau, h_\tau, l_\tau, u_\tau >$ is the data state at the time instant l_τ after $e_{\tau l}$ is satisfied, where $e_{\tau l}$ is the limiting enabling condition [2] . Thus,

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[1] Here a sink state is one where, there is no outgoing transition defined from the composite state

[2] The limiting enabling condition $e_{\tau l}$ is obtained by substituting for the ineqalities in e_τ by equality, e.g. $e_\tau : (T \geq 5 \wedge P \leq 10) \Rightarrow e_{\tau l} : (T = 5 \wedge P = 10)$

$$\overline{\sigma}_\tau = e_{\tau l} + \Delta_x l_\tau$$

For an e_τ defined partially, we need to consider the maximum limit or the limiting condition for data state, of those variables which are not defined in the e_τ. It may be noted that as per the definition of the linear dynamics, the exit condition is not dependent on entry conditions (data states). The entry condition is required to compute the time, a system spend in an activity state. An early entry point is always safe, as it contains all possible situations. However this will give anupper bound of estimation of diagnostic time.

Definition 12. **Early exit measurable data state** $(\overline{\sigma}_{m\tau})$ **of** τ **:**
The early exit measurable data state is be defined as

$$\overline{\sigma}_{m\tau} = e_{\tau l}/\Sigma_m + \Delta_{mx} l_\tau$$

Definition 13. **Early entry data state** $(\overline{\sigma}^+_\tau)$ **of** τ **:**
The early entry data state is be defined as

$$\overline{\sigma}^+_\tau = h_\tau(\overline{\sigma}_\tau)$$

Definition 14. **Early entry measurable data state** $(\overline{\sigma}^+_{m\tau})$ **of** τ **:**
The early entry measurable data state is be defined as

$$\overline{\sigma}^+_{m\tau} = h_\tau(\overline{\sigma}_{m\tau})$$

Similar definitions are also provided for $a \in A$;

Definition 15. **Early exit data state** $(\overline{\sigma}_a)$ **of** a **:**
Early exit data state $(\overline{\sigma_a})$ of a transition $a =< n_a, n^+_a, e_a, h_a, l_a, u_a >$ is the data state at the time instant l_a after e_{al} is satisfied, where e_{al} is the limiting enabling condition. Thus,

$$\overline{\sigma}_a = e_{al} + \Delta_n l_a$$

Definition 16. **Early exit measurable data state** $(\overline{\sigma}_{ma})$ **of** a **:**
The early exit measurable data state is be defined as

$$\overline{\sigma}_{ma} = e_{al}/\Sigma_m + \Delta_{mn} l_a$$

Definition 17. **Early entry data state** $(\overline{\sigma}^+_a)$ **of** a **:**
The early entry data state is be defined as

$$\overline{\sigma}^+_a = h_a(\overline{\sigma}_a)$$

Definition 18. **Early entry measurable data state** $(\overline{\sigma}^+_{ma})$ **of** a **:**
The early entry measurable data state is be defined as

$$\overline{\sigma}^+_{ma} = h_a(\overline{\sigma}_{ma})$$

Equipped with the above definitions, the time sequencing method is now described. it consists two broad steps, namely (i) time sequencing of each node of O resulting in subgraphs of the node and (ii) refining the observer arcs.

4.2 *Subgraph construction of an observer node n*

In the process of time sequencing, all the nodes of O are exploded into a subgraph (sequence) [3] as explained in time sequencing. The nodes in the subgraph are called sub-nodes. The jth sub node of ith node is denoted as n^j_i. The arcs connecting the nodes are the arcs of O. The arcs connecting the subnodes inside the subgraph of a node represent the passage of time. $n_i = n^0_i$, i.e. the 0th sub-node is same as the node. Hence, the **time sequenced observer model** O_T **of an observer** $O =< N, A >$, is an ordered pair represented as

$$O_T =< O, N_T >$$

where

$$N_T = \{< n^k_i, k = 0, 1, 2, ...l_i >, \forall n_i \in N\}$$

More specifically, N_T is a set of sequences of subnodes of the form

$$N_T = \{< n^0_i \xrightarrow{t_0} n^1_i \xrightarrow{t_1} ... \xrightarrow{t_{k-1}(w)} n^{l_i}_i >, \forall n_i \in N\}$$

The last arc, represented as $t_{k-1}(w)$, indicates that it may be a time valued or a waiting arc.

The subgraph of every node $n \in N$ can be constructed by the following steps;

(1) For all the incoming arcs (non-distinguishable measurable transition) a_1, a_2..... into n, find the early entry measurable data state $\overline{\sigma}^+_{mn}$ for the node n.

$$\overline{\sigma}^+_{mn} = \mu(\overline{\sigma}^+_{ma_1}, \overline{\sigma}^+_{ma_2}......) \qquad (1)$$

If the dynamics $\Delta_{mn} > 0$, the operator μ stands for minimum; if $\Delta_{mn} < 0$, then μ is maximum.

(2) Based on the value of $\overline{\sigma}_{mn}$ compute the significant time point of a node. The *significant time points* are as follows.
   - The significant time point of an outgoing transition a is the latest time point at which a becomes invalid. This is denoted as uu_a

     $$uu_a = \frac{e_{al} - \overline{\sigma}^+_{mn}}{\Delta_{mn}} + u_a \;\; for \;\; \Delta_{mn} \neq 0 \qquad (2)$$

     For $\Delta_{mn} = 0$, only w transition is permitted as outgoing transitions for which stay time can not be computed.
   - Similarly, in case we have any transition with an external event as the enabling condition involving some input variable(s), we cannot give any time value to the arc. In this case, the sub node having such an outward transition has to wait for an arbitrary

[3] The subgraph shall always be a sequence. Since we have considered a single valued entry data state (early entry in case of uncertainty), for all outgoing arc there shall be a single uu_a and thus a sequence shall be formed

period of time for the enabling condition to become true. Such transitions are called waiting transition. For any waiting transition a, the significant time point uu_a is set as w.

(3) Each node $n \in N$ of the observer O has a subgraph. Each sub node $n_i^j \subseteq n_i$ of the subgraph represents the refinement of estimate of node n_i, when $n_i^0 = n_i$.

(4) In case, there is any sink state, the subgraph will have the final node with the sink activity state with no arc emanating from it.

4.3 *Trajectory of O_T*

Definition 19. **External Trajectory :**
Any trajectory γ of O is an external trajectory of O_T

Definition 20. **Internal Trajectory of O_T :**
A member of N_T of the form $< n_i^0 \stackrel{t_0}{\rightarrow} n_i^1 \stackrel{t_1}{\rightarrow} ... \stackrel{t_{k-1}(w)}{\rightarrow} n_i^{l_i} >$ is called the internal trajectory of the node n_i. The internal trajectory of node n_i is denoted as γ_{n_i}.

Definition 21. **A Trajectory of O_T :**

A trajectory of O_T, denoted as γ_T, is an external trajectory γ of O followed by the internal trajectory γ_{n_i}, where n_i is the last node of γ.

Significance of expanding the last node is that we do not get any additional information by expanding all nodes, while computing the time delay of a path pertaining to fault diagnosis.

4.4 *Fault diagnosis in O_T*

After construction of O_T, it can happen that some of the subnodes, corresponding to a non-f_i-certain node becomes f_i-certain node. This may be possible because a proper subnode of a node of O, can be $f_i - certain$ and can cause as as a node of O_T. In such cases, with the occurrence of fault f_i an O_T trajectory shall pass through the $f_i - certain$ node. In this perspective, $f_i - certain$ node is redefined as follows;

Definition 22. f_i **-certain node:**
A node n is called f_i-certain node iff
1. $n \subseteq X_{f_i}$, or
2. $(n \cap X_{f_i} = \{x_{f_i}\}\ and\ x_{f_i}\ is\ a\ sink\ state) \wedge (there\ is\ no\ w-transition\ from\ n)$
3. for any non-f_i-certain node n_i, if a subnode $n_i^j \in \gamma_{n_i}$ is f_i-certain subnode by the clause No. 1 and 2 of this definition, it implies that n_i is an f_i-certain node

An f_i-certain node is denoted as $n_{\oplus f_i}$ as before.

However using O_T early detection fault may be possible.

5. DIAGNOSTIC DELAY ESTIMATION

For a diagnosable fault f_i, the diagnostic delay is the maximum length among all the Pf_i-trajectories of O_T, ending into some $n_{\oplus f_i}$ node.

A trajectory length is denoted by a natural number representing the time delay. For waiting transitions the time delay are represented by w, because time delay involved is uncertain.

The maximum time a system can spend in a node n_k for a given pair of incoming and outgoing transitions a_i, a_j is denoted as uu_{n_k} and is computed as below.

(1) Compute the early entry measurable data state $(\overline{\sigma}^+_{ma_i})$ for the incoming transition (a_i) according to the **Definition 18**.

(2) Compute the limiting value of the enabling condition $(e_{a_j l})$ (**Definition 11**), for the outgoing transition (a_j).

(3) the max/min time of stay in a node n_k is computed as

$$uu_{n_k} = \frac{e_{a_j l} - \overline{\sigma}^+_{ma_i}}{\Delta_{mn_k}} + u_{a_j} \tag{3}$$

For the initial node of a trajectory λ, however, the incoming transition is not defined. In such a case the entry data state is same as the early entry measurable data state computed as per **equation 1**.

Let a trajectory γ_T of O_T be of the form $\gamma_T =< n_i, n_{i+1}, ...n_j, n_{j+1}, ...n_k, n_k^0, k_k^1, ..n_k^l >$, where n_k^l is the f_i-certain subnode. If the stay time in every node of γ_T is known, then the time of the trajectory can be computed as;

$$t_{\gamma_{Ti}} = uu_{n_i} + uu_{n_{i+1}} + ... + uu_{n_j} + uu_{n_{j+1}} \\ +....uu_{n_{k-1}} + t_0 + t_1 + ... + t_l$$

where the sequence $t_0 + t_1 + ... + t_l$ pertains to the last node n_k. the quantity gives the worst case diagnostic delay of f_i.

6. CONCLUSION

In this paper, the diagnosability of the discrete time hybrid system (Bhowal *et al.*, 2002*a*) is defined in terms of observer constructed in (Bhowal *et al.*, 2002*b*). The conditions as defined in **Definition 5** are not applicable for most of the practical system. This happens as the real life systems are composition of multiple dynamics. Accordingly a weaker definition of diagnosability, called Pf_i-diagnosability was defined. The observer based diagnoser is further enhanced by time sequencing of observer nodes.

The diagnosability of a system with respect to time sequenced observer is better in terms of detecting additional faults and detecting the faults early. Unlike other method, where the occurrences of transitions are monitored, in the time sequencing observer, their non-occurrences are monitored. Estimation of the diagnostic delay is also discussed here. Based on the present paper an on-line diagnoser, not discussed here, can also be constructed. The diagnostic accuracy can be further improved by constructing diagnoser with delay in line with (Ozveren and Willsky, 1990), (Mukhopadhay *et al.*, 2000*b*). This remains as future work.

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